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Modeling of an Indirect Evaporative Cooler (IEC) using Artificial Neural Network (ANN) approach

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Abstract

Evaluation of performance of an indirect evaporative cooler (IEC) involves solving complex differential and analytical equations. Artificial Neural Networks (ANN) approach provides a simple but powerful tool for predicting the performance of IEC. This paper presents both analytical approach as well as ANN approach in predicting the performance of an IEC. ANN is trained with analytical data using back-propagation learning algorithm with 13 different training algorithms. The logistic sigmoidal function is taken as transfer function. The ANN model is then compared and validated using experimental data from the literature. It was found that the most efficient and most accurate training algorithms were Levenberg-Marquardt (LM) and Bayesian Regularization (BR) back-propagation respectively. After satisfactory training of both the models, the statistical values i.e. R2, RMS, cov, MSE and AIC for the prediction of primary air outlet temperature, ( ) were 0.9999, 0.1786, 1.00, 0.0319 and -3.43 & 0.9999, 0.0546, 0.31, 0.0030 and -5.79 respectively. Similarly, for the prediction of effectiveness ( ) of IEC using the above two models the statistical values were found to be 0.9999, 0.0020, 0.33, 3.8138E-06 and -12.46 & 0.9999, 0.0004, 0.08, 1.9827E-07 and -15.42 respectively. This tool is highly useful for designers to know apriori the performance characteristics of IEC under a given set of environmental conditions without undergoing complicated analysis of the system. This model can also be very useful for designers to predict the energy savings by an IEC.

Keywords: Artificial Neural Networks, Indirect Evaporative cooler, Effectiveness, training.

Introduction

Researchers all over the world are forced to look for alternative ways to reduce energy consumptions as a result of the energy crisis, the whole world is facing. Air conditioning equipments consume a major fraction of the total energy consumption in any economy. Indirect evaporative cooling (IEC) worked by researchers for more than two decades is one of the alternatives which can be used with evaporative cooling and has the potential to replace a conventional air conditioning system working on chlorofluorocarbons. Thus it can not only save useful power but is environment friendly with the advantage of using 100% ventilation air to the conditioned space without increasing the relative humidity of the conditioned space.

IEC works on the principle of heat transfer between two types of air namely primary and secondary air. The air normally supplied from outside air to the conditioned space is termed as primary air. This air is cooled by secondary air with the help of heat transfer passages which are in the form of tubes or plates. Water is sprayed on the surface of passage through which secondary air passes so that heat and mass transfer takes place between secondary air and wetted surface thus reducing the temperature of both. This principle is elucidated with the help of fig1.

Nomenclature

$C_{\max}, C_{\min}$	Maximum and minimum heat capacity rate (W/^{0}C)
C_{wb}	Saturation specific heat (kJ/kg ^{0}C)
i_i, i_o	Enthalpy of air entering and leaving IEC (kJ/kg)
m_p, m_s	Mass flow rate of primary and secondary air (kg/s)
NTU_p, NTU_s	Number of transfer units of primary and secondary air
θ_1, θ_2	Dry bulb temperature of air entering and leaving IEC (^{0}C)
θ_w, θ_{wi}	Effective surface temperature (^{0}C)
$\varepsilon_p, \varepsilon_s$	Cooling effectiveness of primary and secondary air
ε_c	Cooling effectiveness of IEC

One of the first attempts to model IEC analytically with coupled heat and mass transfer processes analogy theory was by Maclaine-Cross and Banks [1]. Kettleborough and Hseih [2] explained a counterflow indirect evaporative cooler with the help of numerical analysis to study the thermal performance of the unit. A reasonable agreement between calculated and measured performance data qualitatively was achieved. A unified theory for equipments working on the principle of evaporative cooling based on the concept of effective surface temperature was given by Webb [3]. Scofield and DesChamps [4] studied characteristics of direct and indirect evaporative cooling units, which utilize plate type air-to-air heat exchanger. The system contains an indirect evaporative cooling unit with a plate type heat exchanger constituting first stage. Ambient air, with low wet bulb temperature is sprayed with water in this unit before it flows in the plate heat exchanger against indoor air taken as primary air, thus resulting in reduction its temperature. Cooling tower is used as the next stage to condition the primary air further. Author found a monthly savings of 30% in the energy cost with this system over conventional refrigeration systems.

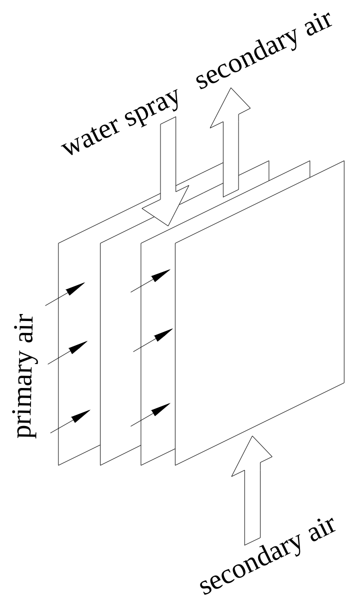

Fig. 1 Model of Indirect Evaporative cooler

Barun et al. [5] suggested effectiveness models of cooling towers based on the principle of saturation specific heat. Chen et al. [6] gave computer simulation program for thermal and hydraulic calculations for IEC performance which was in quite agreement with the experimental results. Peterson and Hunn [7] suggested a model based on analogy theory for an IEC and compared it with experimental data. Erens and Dreyer [8] proposed three analytical models and showed that the optimum shape of the cooler unit would result in a primary to secondary air velocity ratio of about 1.4, taking the assumption that the primary and the secondary air mass flow rates are the same and that the same plate spacings used are on the primary and secondary sides. Peterson [9] gave a simple but powerful model for calculating the theoretical performance of indirect evaporative coolers. Halasz [10] put forward a generalized model based on non-dimensional parameters for all types of evaporative cooling devices and established a rating procedure for these devices. Guo and Zhao [11] studied the effects of various parameters on the performance of an IEC with the help of numerical simulation. Chengqin and Hongxing [12] developed an analytical model for the indirect evaporative cooling with parallel and counter flow configurations. Within relatively narrow range of operating conditions, humidity ratio of air in equilibrium with water surface was assumed to be a linear function of the surface temperature. In this model, effects of spray water evaporation, spray water temperature variation along the heat exchanger, non unity surface wettability and Lewis factor were taken into consideration. A good agreement between results of analytical solutions and of numerical integrations was found. Heidarinejad and Bozorgmehr [13] developed a model of indirect evaporative cooling starting from the governing equations of heat and mass transfer in primary and secondary air and water flows. Factors affecting performance of IEC such as mass flow rates, geometry and flow configuration has been investigated. Authors found that cooling efficiency depends considerably upon mass flow rates ratios of primary and secondary air flows and spacing between plates of wet and dry passages.

From the above survey of previous work it is obvious that to predict the performance of an IEC accurately requires solving conventional mathematical models consisting of complex differential and analytical equations. Artificial Neural Networks (ANN) gives not only an accurate but viable approach for modeling an IEC. This powerful technique is based on learning technique of human brain. ANN model approach is particularly useful for systems which are complex and its behavior is non-linear. It works by establishing a relationship between input and output variables with the help of neurons.

In the recent past there has been a considerable growing interest amongst researchers in using ANN for modeling air conditioning devices. Sozen et. al. used ANN model approach for thermodynamic analysis of ejector absorption cycle [14], for calculation for the thermodynamic properties of an alternative refrigerant (R508b)[15], (R407c)[16] and ozone friendly refrigerant/absorbent couples[17], for determining the efficiency of flat-plate solar collectors[18], for predicting the performance of a solar-driven ejector-absorption cycle[19], for the performance analysis of ejector absorption heat pump using ozone safe fluid couple[20] and for determining the properties of liquid and two phase boiling and condensing of two refrigerant couples i.e. methanol-LiBr and methanol-LiCl [21]. Pacheco-Vega et al. 2001, predicted heat rates of heat exchangers used for refrigeration applications [22] and for humid air-water heat exchangers[23] using ANN model and correlations. Sencan et al. used ANN prediction model to determine the thermodynamic properties of four alternative refrigerant or absorbent couples namely LiCl-H_2O and LiBr + $LiNO_3$ + LiI +LiCl-H_2O [24] & thermodynamic properties of LiBr-water and LiCl-water solutions [26]. Sencan used Linear Regression and M5'Rules models within data mining process and ANN model for thermodynamic evaluation of ammonia-water absorption refrigeration systems [26]. Yang et al. [27] used ANN model to predict optimal start time for heating system in building. Kalogirou [28]-[29] reviewed the application of ANN for energy systems. Kalogirou and Bojic [30] used ANN model the prediction of the energy consumption of a passive solar building. Kalogirou et al [31] predicted the performance of a thermosiphon solar water heater using ANN model. Kalogirou [32] predicted the long-term performance of forced circulation solar domestic water heating systems with the help of ANN model.

Ertunc and Hosoz with the help of ANN predicted the performance of evaporative condenser [33] and an automobile air conditioning system [34]. Hosoz et al. [35] gave ANN prediction model of cooling tower. Jambunathan et al. [36] evaluated convective heat transfer coefficients, Chouai et al. [37] predicted the thermodynamic properties of R134a, R32 and R143a, Manohar et al. [38] predicted the performance of double effect vapour absorption chiller, Atthajariyakul and Leephakpreeda [39] computed thermal comfort index for HVAC systems, Qi et al. [40] simulated shower cooling tower and Islamoglu [41] predicted the performance of non-adiabatic capillary tube suction line heat exchanger using ANN models.

In this work, ANN model approach is used to predict the performance of IEC. Analytical data obtained from Engineering Equation Solver (EES) [42] is used to train the ANN model under summer conditions of Bhopal, India. The ANN model can be used to predict output primary air temperature and effectiveness of IEC. In this work the most accurate and efficient ANN model is found using different training algorithms. The ANN model is then validated using limited experimental data.

2. Artificial Neural Networks

Artificial Neural Networks or popularly known as ANN is an attempt to mimic the learning process of human brain. ANN consists of a group of a number of interconnected cells called as neurons with weights working together to create artificial intelligence or 'learning' in machines. ANN consists of primarily three layers: input, hidden and output layer. The input and output layer consists of a collection of neurons representing input and output variables. Similarly the hidden layer also consists of a series of definite neurons and is connected in between the above two layers. Each neuron, m in a layer is connected to all the neurons in the consecutive layers with some weight which represents the strength of a connection.

$$m = \sum_{k=1}^{n} w_k x_k + \beta \qquad (2.1)$$

where, n = number of neurons in the subsequent layer,

w_k = weights of the respective connections, and

β = bias for the neuron.

Firstly training is being imparted to the ANN model with the help of known set of data patterns which the network 'learns' continuously by adapting its weights and biases through an activation function, A. Thus the network computes output according to the following equation [43]:

$$A(m) = A\left[\sum_{k=1}^{n} w_k x_k + \beta\right] \qquad (2.2)$$

Induction of activation functions makes it a more versatile and powerful tool and makes it capable to represent even complex non-linear physical models. A number of activation or transfer functions (TF) are used to connect amongst neurons of different layers such as sigmoidal, tansigmoidal, purelinear, logsigmoidal, hardlimit, positive linear, radial basis, triangular basis, soft linear etc.

The network is thus trained until the error is reduced to a great extent and is acceptable for a particular task. The 'intelligent' ANN is now ready to predict accurate from a given set of input data same no of variables. There are no hard and fast rules for the construction of neural networks. It is dependent on past experience or through trial and error method.

ANN is trained by a suitable algorithm for a specific problem. Although a number of training algorithms are available like but the most popular is feed forward back propagation algorithm.
The performance of an ANN model can be checked with the help of following statistical functions. The coefficient of multiple determinations (R^2) according to [44] is defined as:

$$R^2 = 1 - \frac{\sum_{k=1}^{n} (u_{a,k} - u_{p,i})^2}{\sum_{k=1}^{n} (u_{a,k})^2} \qquad (2.3)$$

where, $u_{p,k}$ is the values predicted by the ANN model and

$u_{a,k}$ is the actual analytical values of a variable.

The root mean square error (RMSE) and coefficient of variation (cov) are defined as [44]:

$$RMSE = \sqrt{\frac{\sum_{k=1}^{n}(u_{a,k} - u_{p,k})^2}{n}} \tag{2.4}$$

where, n is the no of observations or data patterns

$$\mathrm{cov} = \frac{RMSE}{\left|\bar{u}_a\right|} \times 100 \tag{2.5}$$

where, $\bar{u}_a$ is the mean of actual values of a variable.

The Akaike's Information Criterion (AIC) proposed by Hirotsugu Akaike is defined as

$$AIC = \ln(s_m^2) + \frac{2m}{n} \tag{2.6}$$

where, s_m^2 = (sum of squared residuals for a model with m parameters)/n,

n = no. of observations and

m = no of output variables

3. Analytical model approach to IEC

The following equations are derived from Peterson [9] for the analysis of indirect evaporative cooler.

Saturation specific heat can be defined as:

$$C_{wb} = \frac{(i_o - i_i)}{(\theta_{wo} - \theta_{wi})} \tag{3.1}$$

The outlet temperature of air from IEC θ_2 as given by [9] is

$$\theta_2 = \theta_1 - \frac{C_{\max}}{C_{\min}}(\theta_{wo} - \theta_{wi}) \tag{3.2}$$

where,

$C_{\min} = m_p c_p$ and $C_{\max} = m_s c_{wb}$

Generally the performance of an IEC is expressed in terms of cooling effectiveness which can be defined as below

$$\varepsilon_c = \left\{\frac{\theta_1 - \theta_2}{\theta_1 - \theta_{wi}}\right\} \tag{3.3}$$

After analysis the required expression for cooling effectiveness as given by [9] is

$$\varepsilon_c = \frac{1}{\frac{1}{\varepsilon_p} + \frac{1}{\varepsilon_s}\left\{\frac{C_{\max}}{C_{\min}}\right\}} = \frac{1}{\frac{1}{\varepsilon_p} + \frac{1}{\varepsilon_s}\left\{\frac{m_p c_p}{m_s c_{wb}}\right\}} \tag{3.4}$$

where, $\varepsilon_p = 1 - e^{-NTU_P} = \frac{C_{\max}}{C_{\min}}\left\{\frac{\theta_{wo} - \theta_{wi}}{\theta_1 - \theta_w}\right\}$ (3.5)

$$\varepsilon_s = 1 - e^{-NTU_s} = \left\{ \frac{\theta_{wi} - \theta_{wo}}{\theta_{wi} - \theta_w} \right\} \tag{3.6}$$

4. Application of ANN to IEC

Determination of performance characteristics of an IEC is one of the major problems due to the complex heat and mass transfer phenomena. Analytical results of a simplified model of IEC as suggested by [9] are obtained with the help of Engineering Equation Solver (EES) for different atmospheric conditions during summer season of Bhopal, India. The primary and secondary air mass flow rates are varied in the range of 0.1-2.5 kg/s, inlet dry bulb temperature of outside air is varied from 20-45^{0}C and the variation of relative humidity is taken from 10-70%.

A number of ANN models are trained and tested with different algorithms, details of which are shown in the table 1. The input and output data sets are normalized in the range of (0, 1) before training. The input layer, hidden layer and output layer of the ANN model contains 4, 10 and 2 neurons respectively as shown in figure 2. The transfer function used for all the layers is logistic sigmoidal function which is given by:

$$f(x) = \frac{1}{1+e^{-x}} \tag{4.1}$$

Table 1. List of training algorithms used for ANN models

S. No	**Training Algorithms**	**Expanded form**
1	**trainbfg**	BFGS quasi-Newton backpropagation
2	**tranbr**	Bayesian regularization.
3	**traincgb**	Powell-Beale conjugate gradient backpropagation
4	**traincgf**	Fletcher-Powell conjugate gradient backpropagation.
5	**traincgp**	Polak-Ribiere conjugate gradient backpropagation
6	**traingd**	Gradient descent backpropagation
7	**traingda**	Gradient descent with adaptive lr backpropagation
8	**traingdm**	Gradient descent with momentum backpropagation.
9	**traingdx**	Gradient descent with momentum and adaptive lr backpropagation
10	**trainlm**	Levenberg-Marquardt backpropagation
11	**trainoss**	One-step secant backpropagation
12	**trainrp**	Resilient backpropagation (Rprop)
13	**trainscg**	Scaled conjugate gradient backpropagation

The most prominent variables which influences the performance of an IEC are primary and secondary mass flow rate of air (m_p & m_s), ambient dry bulb and wet bulb temperature(θ_1 & θ_w). Thus these four variables are taken as input variables.

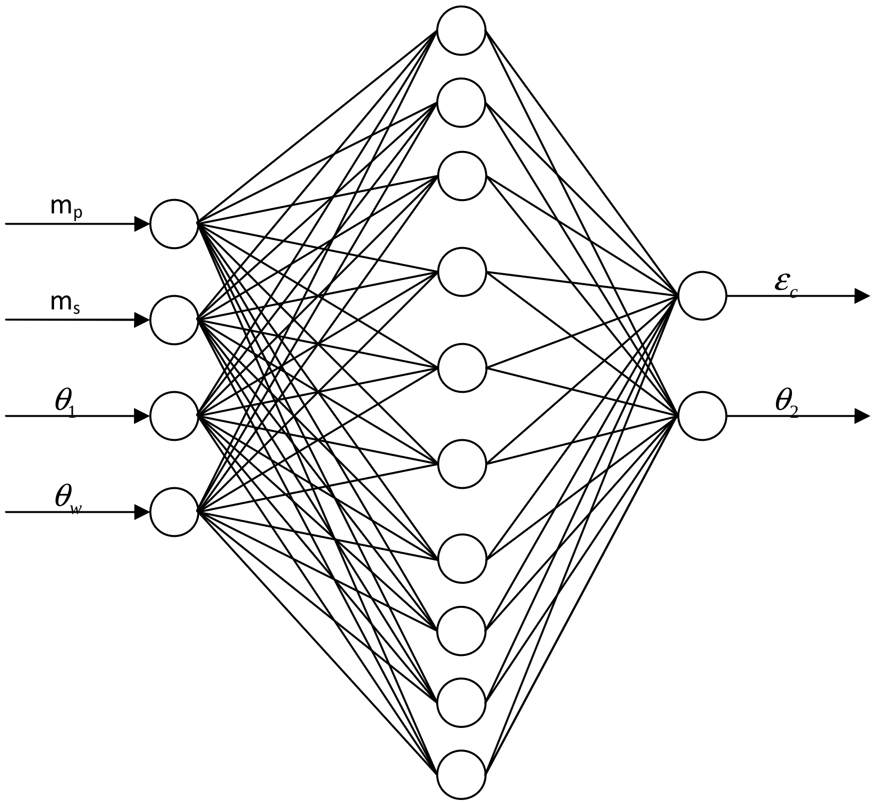

Fig. 2: Network Architecture of ANN model of an IEC.

The outlet temperature of air (θ_2) and effectiveness (ε_c) are taken as output variables for the ANN model. The network architecture is shown in fig 2.

Results and Discussion

With the increasing demands for electricity, depleting fossil fuels and depleting ozone layer due to the use of chlorofluorocarbons(CFC's) has forced researchers to look for alternative and eco-friendly technologies for air conditioning. Indirect cooling not only saves valuable electricity but is eco-friendly takes away heat from the conditioned space without increasing the relative humidity. Thus designers require performance data for an IEC according to different climatic conditions to design efficient systems.

In this work an IEC has been modeled analytically as well as with ANN model approach. The ANN model was trained with atmospheric conditions of Bhopal, India during the summer season (April-June) with the help of 1300 data sets obtained by solving with the help of EES. 13 training algorithms as shown in table 4.1 were used to model ANN and thus then the most efficient and accurate one are determined. The ANN model is trained with the help of m-file programming under MATLAB 7.0 [45]. After the network is sufficiently trained, it is tested with 50 data sets to get predictions and is then compared with analytical results.

Four input parameters namely mass flow rate of primary air and secondary air, m_p and m_s & ambient dry bulb and wet bulb temperature θ_1 and θ_w were used to obtain two outputs variables namely effectiveness ε_c and θ_2.

Statistical values are calculated for each ANN model with a suitable test data which is shown in table 2. Table 3 shows statistical values during training of various ANN models. The various performance characteristics during training like mean square error with regularization (MSEREG), mean square error (MSE), mean absolute error (MAE) and sum squared error (SSE) depicts how well the ANN model is trained.

It can be observed that the model is trained very efficiently and accurately using LM and BR training algorithms. Although LM is very fast as can be observed from the no of epoch is the least; but the only drawback is that it requires lot of computer memory. On the other hand BR algorithm requires less of it and is very accurate as compared to LM but it is not as efficient as it is evident that it requires 1300 epoch as compared to 40 for LM.

After satisfactory training the performance of each ANN model is tested with the help of test data which is summarized in Table 4 and 5. The ANN model is considered superior as the statistical values like RMS, cov and MSE approaches zero and R^2 value approaches one. AIC gives the measure of the goodness of fit of an estimated statistical model. The model having the lowest AIC being is considered the best one. It is obvious from both the tables that the BR algorithm is most accurately trained as the statistical values i.e R^2, RMS, cov, MSE and AIC values are 0.9999920, 0.0546, 0.31, 0.0030 and -5.79 for predicting θ_2 & 0.9999995, 0.0004, 0.080, 1.9827E-07 and -15.42 for predicting ε_c. The next most accurate model is using LM algorithm. Fig 3 and 4 shows the training curve for BR and LM backpropagation training algorithm. The analytical output and ANN output are compared and are shown in Fig 5-8. The ANN model is validated using experimental data given in [9]. A comparison between the experimental performance and that with ANN model is shown in fig 9-10.

Table 2 Sample of the testing data used for various ANN models

Patterns	**m_p**	**m_s**	**θ_1 (^{0}C)**	**θ_w (^{0}C)**	**θ_2 (Analytical)**	**ε_c (Analytical)**	**θ_2 (Predicted by ANN, ^{0}C)**	**ε_c (Predicted by ANN)**	**Error(θ_2)**	**Error(ε_c)**
1	1.1	0.8	31.8	7.1	15.93	0.6443	15.95	0.6436	-0.02	0.0007
2	0.8	1.3	32.7	6.7	12.16	0.791	12.19	0.7904	-0.03	0.0006
3	1.9	0.8	34.3	6.1	19.52	0.5244	19.55	0.5243	-0.03	1E-04
4	1.0	1.8	34.7	5.8	11.47	0.8027	11.59	0.8027	-0.12	0
5	2.4	2.2	34.9	5.7	14.85	0.6856	14.91	0.6855	-0.06	1E-04
6	2.1	1.6	35.4	5.6	16.07	0.6492	16.04	0.6491	0.03	1E-04
7	2.2	2.2	34.9	5.7	14.36	0.7023	14.43	0.7021	-0.07	0.0002
8	1.3	2.4	35.6	5.4	11.27	0.8049	11.44	0.8048	-0.17	1E-04
9	0.8	1.7	36.1	5.1	10.58	0.824	10.66	0.8236	-0.08	0.0004
10	1.6	1.5	36.6	5.0	14.89	0.6882	14.87	0.6877	0.02	0.0005

Table 3 Statistical values obtained during training of various ANN models

S. No	Training Algorithm	MSEREG	MSE	MAE	SSE	Epochs
1	trainbfg	2.66E-05	2.96E-05	0.0036	0.0031	3600
2	trainbr	2.25E-07	2.50E-07	3.62E-04	2.60E-05	1300
3	traincgb	0.0034	0.0038	0.0446	0.3981	130
4	traincgf	0.0035	0.0038	0.0448	0.3987	300
5	traincgp	0.0074837	0.0053	0.0557	0.5464	800
6	traingd	0.0056105	0.0034	0.0416	0.3557	1E+06
7	traingda	0.0059	0.0039	0.0444	0.04032	42000
8	traingdm	0.0031	0.0035	0.0422	0.398	1E+05
9	traingdx	0.00509	0.0449	0.0449	0.3978	20000
10	trainlm	3.13E-06	0.0013	3.62E-04	3.62E-04	40
11	trainoss	0.0051	0.0446	0.3975	0.3975	1100
12	trainrp	0.00507805	0.0038	0.3976	0.3976	2000
13	trainscg	0.00503897	0.0445	0.398	0.398	1000

where,
MSEREG: mean square error with regularization
MAE: mean absolute error
SSE: sum squared error

Table 4 Statistical values of various ANN models to predict primary air outlet temperature, θ_2 from IEC

S. No.	Training Algorithm	R^2	RMS	cov	MSE	AIC
1	**trainbfg**	0.9990990	0.5852	3.28	0.3425	-1.05
2	**trainbr**	0.9999920	0.0546	0.31	0.0030	-5.79
3	**traincgb**	0.9714471	3.3359	18.71	11.1280	2.43
4	**traincgf**	0.9714807	3.3369	18.72	11.1349	2.43
5	**traincgp**	0.9102609	5.3041	29.75	2.8328	3.36
6	**traingd**	0.9806052	2.7362	15.35	7.4867	2.03
7	**traingda**	0.9757449	2.6090	16.42	-0.4390	1.94
8	**traingdm**	0.9749340	3.1396	17.61	9.8573	2.31
9	**traingdx**	0.9744041	2.6840	16.90	-0.4495	1.99
10	**trainlm**	0.9999141	0.1786	1.00	0.0319	-3.43
11	**trainoss**	0.9759299	2.5991	16.36	-0.4405	1.93
12	**trainrp**	0.9765177	2.5652	16.15	-0.4343	1.90
13	**trainscg**	0.9745877	2.6740	16.83	-0.4490	1.99

Table 5 Statistical values of various ANN models to predict effectiveness from an IEC , ε_c

S. No.	Training Algorithm	R^2	RMS	cov	MSE	AIC
1	**trainbfg**	0.9999356	0.0050	0.84	2.4835E-05	-10.58
2	**trainbr**	0.9999995	0.0004	0.080	1.9827E-07	-15.42
3	**traincgb**	0.9829715	0.0809	13.68	0.006545	-5.01
4	**traincgf**	0.9829424	0.0810	13.69	0.006554	-5.01
5	**traincgp**	0.9814795	0.0877	14.83	-0.014531	-4.85
6	**traingd**	0.9841170	0.0781	13.20	0.006093	-5.08
7	**traingda**	0.9999981	0.0824	13.39	0.043383	-4.97
8	**traingdm**	0.9845065	0.0771	13.03	0.005937	-5.11
9	**traingdx**	0.9999989	0.0674	10.96	-0.001296	-5.37
10	**trainlm**	0.9999901	0.0020	0.33	3.8138E-06	-12.46
11	**trainoss**	0.9999989	0.0674	10.96	-0.001279	-5.37
12	**trainrp**	0.9999989	0.0674	10.96	-0.001280	-5.37
13	**trainscg**	0.9999989	0.0674	10.96	-0.001284	-5.37

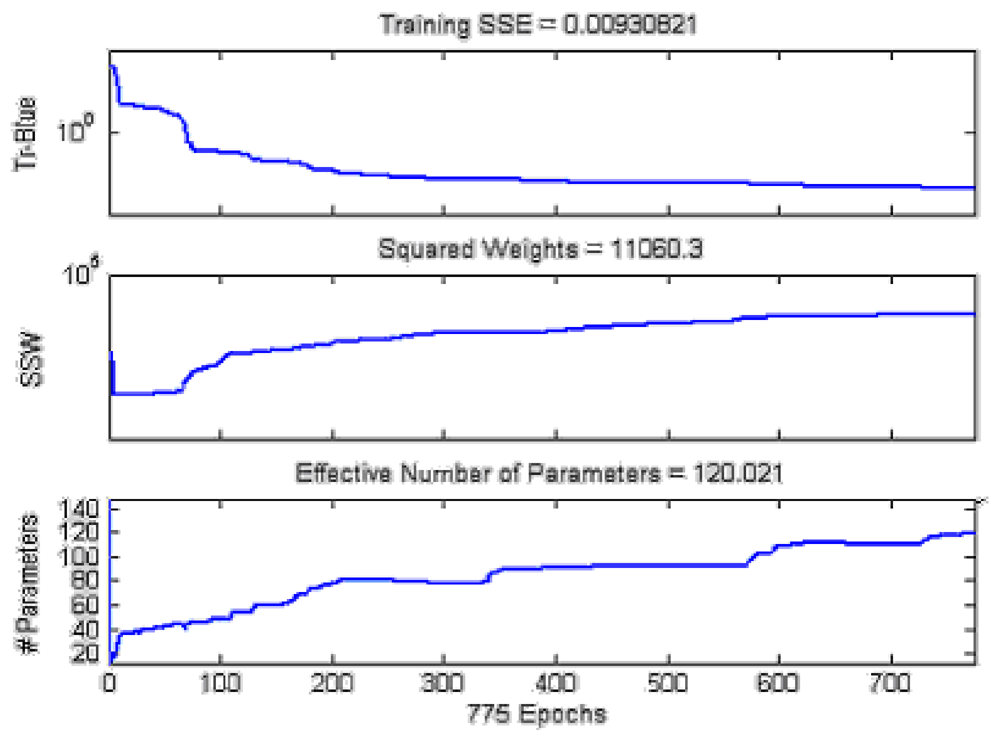

Fig. 3 Training curve during ANN training of IEC with trainbr (Bayesian regularization) backpropagation Algorithm

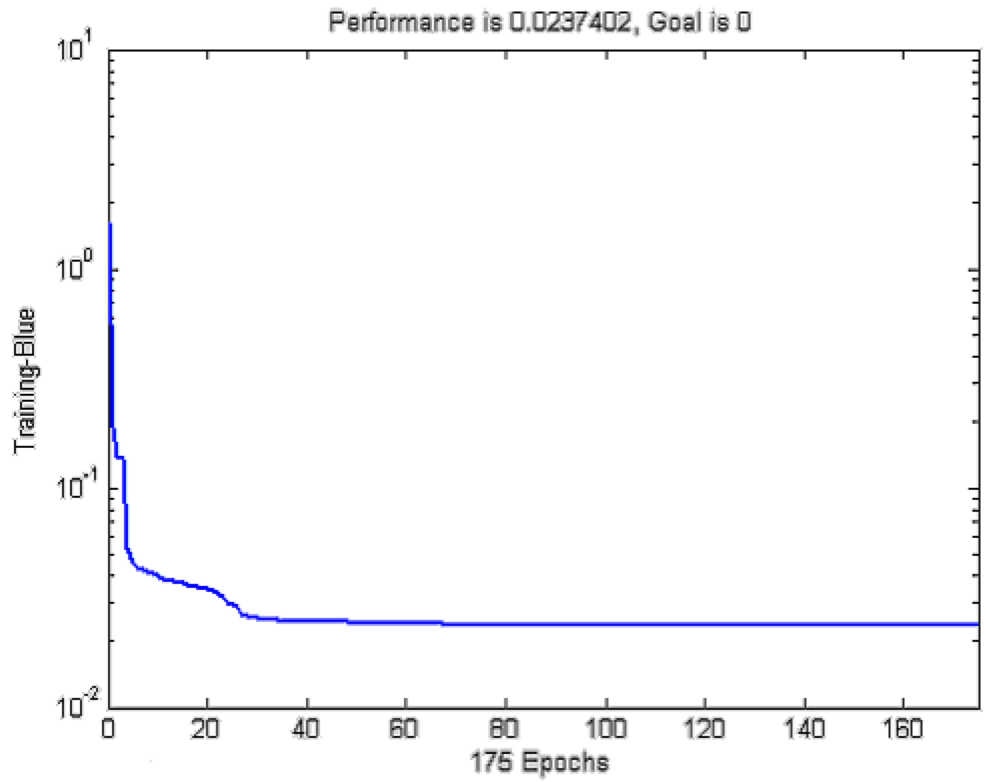

Fig. 4 Training curve during ANN training of IEC with trainlm (Levenberg Marquardt) backpropagation Algorithm

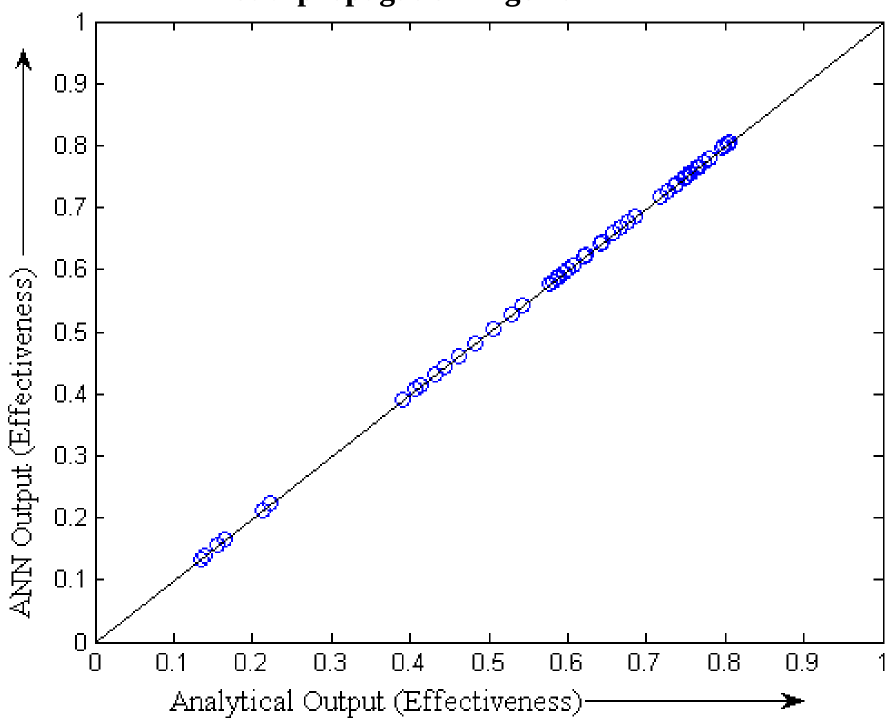

Fig. 5: Comparison of analytical results with ANN model output being trained with Levenberg Marquardt back Propagation algorithm

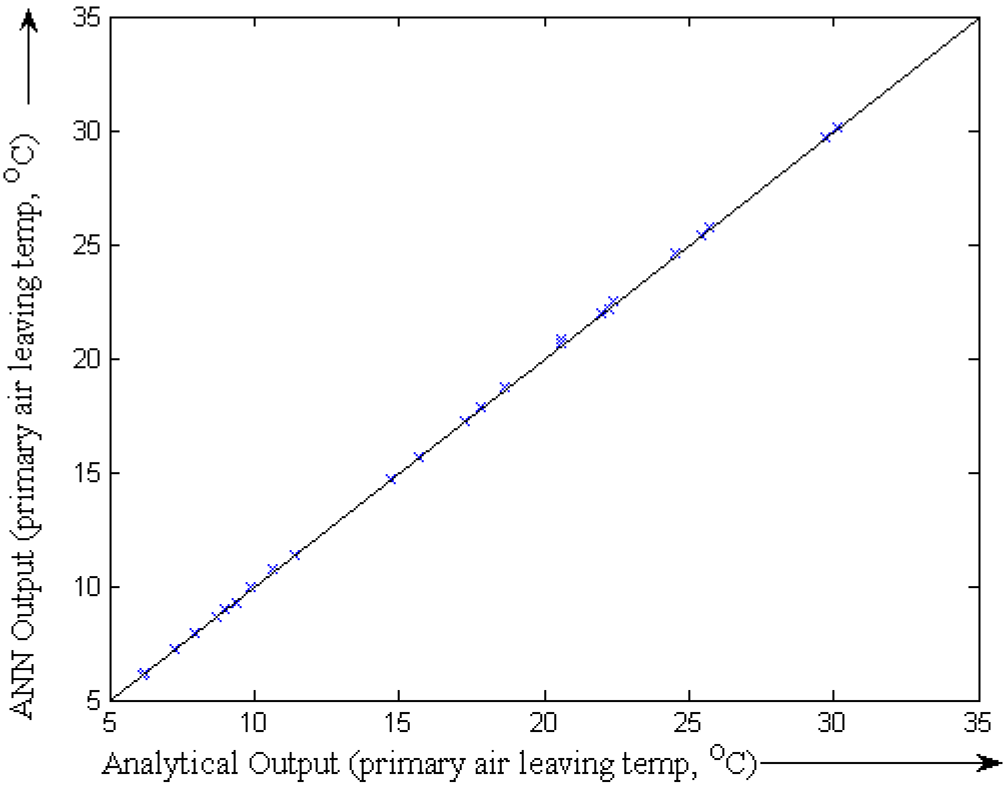

Fig. 6: Comparison of analytical results with ANN model output being trained with Levenberg Marquardt back propagation algorithm

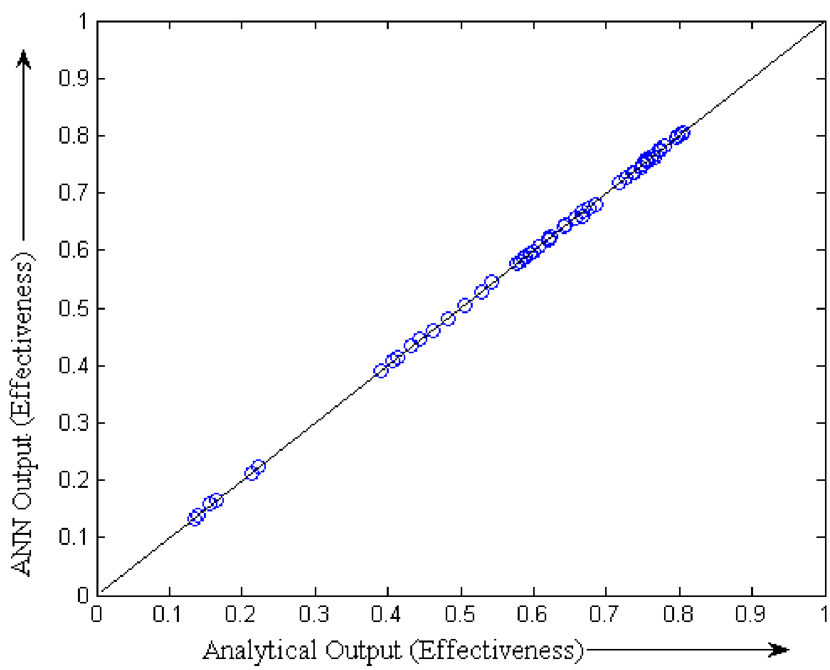

Fig. 7: Comparison of analytical results with ANN model output being trained with Bayesian Regularization (BR) back-propagation algorithm

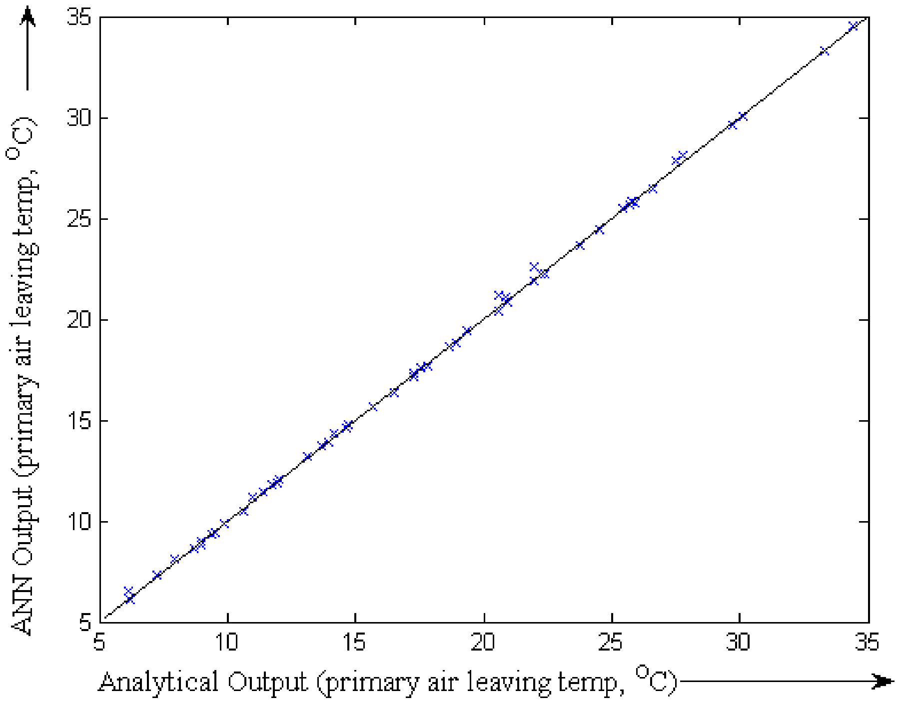

Fig. 8: Comparison of analytical results with ANN model output being trained with Bayesian Regularization (BR) Back-propagation algorithm

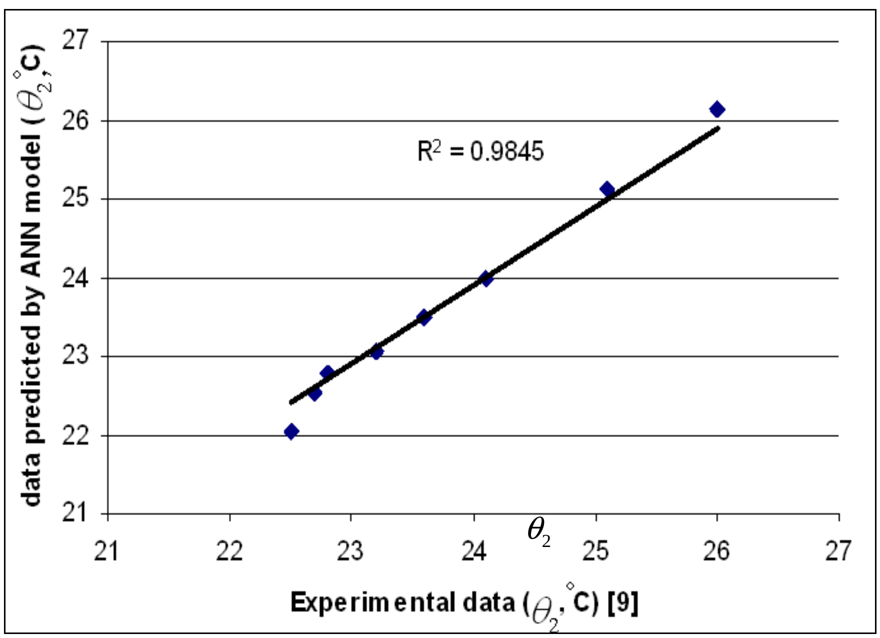

Figure 9: Comparison of experimental results with ANN model output trained with BR algorithm

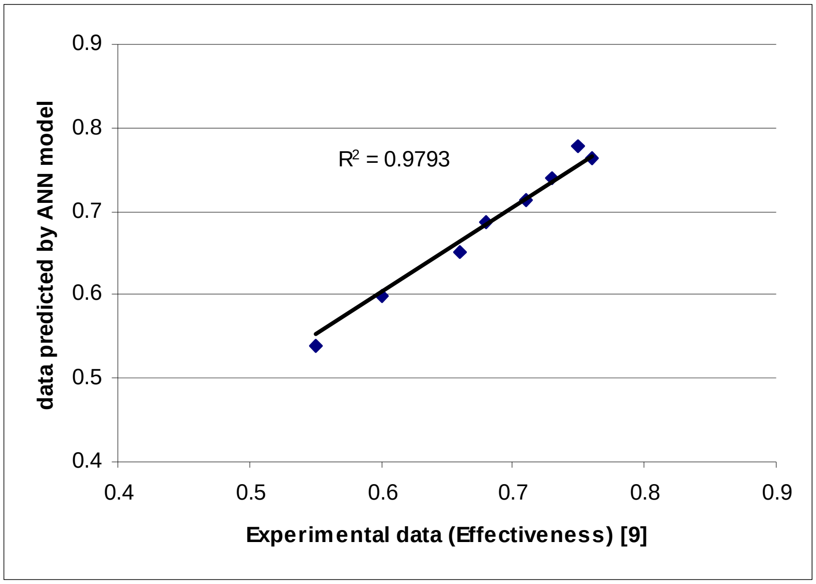

Fig. 10: Comparison of experimental results with ANN model output trained with BR algorithm

Conclusion

This work shows the usefulness of an intelligent way to predict the performance of indirect evaporative cooler using artificial neural networks. Different ANN models were trained and tested with analytical results for an IEC. The results were obtained for the summer season of a typical meteorological year of Bhopal, India, using Engineering Equation Solver. The model was then validated with a limited experimental data. It was found that the most efficient training algorithm for modeling an indirect evaporative cooler was Levenberg Marquardt followed by Bayesian regularization backpropagation algorithm. The LM algorithm although is very fast but in training large data patterns it requires large memory. This deficiency can be overcome by using BR algorithm.

Excellent result proves that artificial neural networks have the capability to predict the performance of IEC very accurately as compared to the conventional methods of modeling. Also, ANN has the superiority of simplicity, adaptability and robustness over classical methods.

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